Components of Economic Policy Uncertainty and Predictability of US Stock Returns and Volatility: Evidence from a Nonparametric Causality-in-Quantile Approach

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Abstract

Predicting stock returns has significant implications for asset allocation, investment performance, and testing market efficiency. To this end, we examine whether U.S. stock returns and volatility can be predicted from a comprehensive set of financial and economic uncertainty indicators as well as migration-related uncertainty measures. We employ the

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nonparametric causality-in-quantile approach which is robust to misspecification errors since it captures nonlinearities in returns distribution. Our decision to use this approach is motivated by the presence of nonlinearity in our examined series, suggesting that the Granger causality test based on a linear framework is likely to suffer from misspecification. Our findings reveal that aggregate economic policy uncertainty (EPU) together with its different sub-components possess predictive information for U.S. stock returns and volatility barring few cases. In general, the prediction is strongest for returns volatility than for returns. Moreover, we document the ability of the recently developed migration-related EPU and migration fear measures in predicting financial market volatility. Our study therefore, provides evidence that level of aggregate and sub-components of policy uncertainty tends to cause stock market returns, and primarily, volatility.

Keywords: Economic Policy Uncertainty; Migration; Stock Prices; Nonparametric Quantile Causality; Volatility
JEL Classification: C22, E6, G1

1 – Introduction

Predicting stock market returns and volatility is of utmost importance to policy makers and portfolio managers when reflecting on future corporate health and investment prospects (Poon and Granger, 2003; Rapach and Zhou, 2013). In this regard, there is a growing post-financial crisis literature that has analysed the role of uncertainty on predicting international stock markets (see for example, Antonakakis *et al.*, (2013, In press), Bhagat *et al.*, (2013), Kang and Ratti (2013, 2015), Gupta *et al.*, (2014), Brogaard and Detzel (2015), Chang *et al.*, (2015), Chuliá *et al.*, (2015), Han *et al.*, (2015), Jurado *et al.*, (2015), Mensi *et al.*, (2014, forthcoming), Redl (2015), Sum (2012a, 2012b, forthcoming), Balcilar *et al.*, (2015b, c, forthcoming a), Momim and Masih (2015), Rossi and Sekhposyan (2015), Bekiros *et al.*, (2016, forthcoming), Li *et al.*, (2016), Aye *et al.*, (forthcoming a, b), and Christou and Gupta (2016)).

Theoretically, there are direct and indirect channels through which uncertainty can affect the stock market. In terms of the direct route, Bloom (2009) develops a standard firm-level model with a time-varying second moment of the driving process and a mix of labor and capital adjustment costs. Then the author shows that firms only hire (fire) and invest (disinvest) when business conditions are sufficiently good (bad). In addition, the model yields a central region of inaction in hiring and investment space (due to nonconvex adjustment costs), which in turn, expands when uncertainty is high, with firms becoming more cautious in responding to business conditions. This line of thinking was vindicated empirically by Kang *et al.*, (2014). As far as the indirect channel goes, recent papers by Mumtaz and Zanetti (2013) and Carriero *et al.*, (2015), following on the early works of Bernanke (1983), Dixit and Pindyck (1994), develop general equilibrium models to show that, besides productivity and/or policy shocks, various forms of policy-generated uncertainty leads to business cycle fluctuations.[1] And given that, asset

[1] International empirical evidence on how movements in uncertainty affect economic activity can be found in: Alexopoulos and Cohen (2009), Bloom (2009), Bachmann and Bayer (2011), Knotek and Khan (2011), Aastveit *et al.*, (2013), Bachmann *et al.*, (2013), Colombo (2013), Jones and Olson (2013, 2015), Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Benati (2014), Karnizova and Li (2014), Alessandri and Mumtaz (2014), Balcilar *et al.*, (2015a, forthcoming b), Bonga-Bonga *et al.*, (2015), Caggiano *et al.*, (2014a,

returns are functions of the state variables of the real economy, fluctuations in it due to policy uncertainty is likely to affect the stock market.

Since uncertainty is unobservable, obtaining an appropriate measure for it is not straight-forward. Two primary approaches in this regard are: (i) News-based approach of Brogaard and Detzel (2015), and Baker *et al*., (2015), whereby the authors perform month-by-month searches of newspapers for terms related to economic and policy uncertainty to construct their measure of economic policy uncertainty; (ii) Alternatively, Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Alessandri and Mumtaz (2014), Mumtaz and Theodoridis (2014, 2015), Carriero *et al*., (2015) Jurado *et al*., (2015), Ludvigson *et al*., (2015), and Rossi and Sekhposyan (2015) recover measures of uncertainty from stochastic volatility in the error structure of estimated structural VAR models.[2] While there exists no clear-cut consensus in terms of which approach to use in constructing measures of uncertainty, the news-based measures of uncertainty, as developed by Baker *et al*., (2015), seems to have gained tremendous popularity in various applications in macroeconomics and finance.[3] This is most likely due to the fact that data (not only for the US, but also other European and emerging economies) based on this approach is easily and freely available for use, and does not require any complicated estimation of a model to generate it in the first place. In addition, besides the aggregate measure of uncertainty, which is what the above literature has primarily used, Baker *et al*., (2015) has also developed indices that capture uncertainty related to various forms of economic policy. It is not unlikely that different economic policies will affect the stock market differently. In addition, to the recently developed components of policy uncertainty, Baker *et al*., (2015) has also developed migration-related measures (migration fear and migration-related EPU). Given that a large population inflow creates uncertainty about social,

2014b, 2015), Mumtaz and Theodoridis (2015, forthcoming), Baker *et al*., (2015), Carriero *et al*., (2015), Jurado *et al*., (2015), Redl (2015), Rossi and Sekhposyan (2015), Sin (2015), and Netšunajev and Glass (2016).

[2] Though not as technical like the structural VAR based approaches, Bali *et al*., (2015) recovers a measure of uncertainty based on a weighted average of the dispersion of many macroeconomic variables.

[3] See Strobel (2015) for a detailed review of alternative measures of uncertainty.

political and economic outcomes (Baker *et al*., 2015; Boeri *et al*., 2015), migration related indices could also incorporate important predictability for stock market returns and volatility. Note that, given the globalized financial markets, it is possible that migration related fears in not only the domestic economy, but also other important financial markets like the UK, France and Germany could also affect the US stock market return and volatility.

Against this backdrop, for the first time in the literature,[4] we employ the nonparametric causality-in-quantile test proposed by Balcilar *et al*. (2016, forthcoming a) to analyse whether aggregate EPU as well as its various components can predict monthly and quarterly stock returns and volatility of the US economy over the period of 1985:01-2015:12 and 1990:01-2015:04 respectively. This test of Balcilar *et al*., (2016, forthcoming a) combines the frameworks of the *k*-th order causality of Nishiyama *et al*. (2011) and quantile causality of Jeong *et al*. (2012), and hence, can be considered to be a more general version of the former. The causality-in-quantile approach has the following novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series; this could prove to be particularly important, as it is well known that the stock market display nonlinear dynamics - something we show below as well, not only for the stock returns on its own, but also in its relationship with the various measures of uncertainties. Secondly, via this methodology, we are able to test for not only causality-in-mean (1st moment), but also causality that may exist in the tails of the joint distribution of the variables, which in turn, is particularly important if the dependent variable has fat-tails – something we observe with negatively skewed (monthly and quarterly) stock returns.[5] Finally, we are also able to investigate causality-in-variance, i.e. volatility spillovers, as some times when causality in the conditional-mean may not exist, yet higher order interdependencies might emerge.

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[4] Antonakakis *et al*., (In press) used the causality test of Jeong *et al*., (2012) to analyze the predictability of sustainability index emanating from aggregate and components of EPU. But this study did not analyze the conditional distribution of volatility as well as the migration related EPUs.

[5] The Jarque-Bera statistic for monthly (quarterly) stock returns data was 662.2952 (576.0241) rejecting the null of normality with a p-value of 0.00 (0.00).

At this stage, it is important to point out that our paper can be considered as an extension of the work of Bekiros *et al.,* (2016), which analysed the impact of aggregate uncertainty on US stock returns and volatility using the Nishiyama *et al.,* (2011) approach. We however, add to this paper by looking at not only aggregate uncertainty, but also components of uncertainty. This is more informative, since it will tell us what forms of uncertainty matters the most in predicting stock returns and volatility, and also, in an indirect way, which components drive aggregate uncertainty. More importantly, we study the entire conditional distribution of stock returns and volatility using the causality-in-quantile approach, which is of course more general (and powerful) than the Nishiyama *et al.,* (2011) method. This is something we show to be the case, since we detect predictability of both returns and volatility, while in Bekiros *et al.,* (2016), causality from uncertainty was primarily restricted to volatility. The rest of the paper is organised as follows, we present the causality-in-quantile method in section 2. Section 3 discusses the data and empirical findings, and section 4 concludes.

2 - Methodology

We investigate the predictability of a broad set of financial and economic indicators and migration-related measures on U.S. stock returns using a novel approach proposed by Balcilar *et al*. (2016, forthcoming a). Their method combines the frameworks of Nishiyama *et al*. (2011) and Jeong *et al*. (2012). We denote stock returns as (y_t) and the different predictors as (x_t). Following Jeong *et al*. (2012), the quantile-based causality is defined as follows:[6] x_t does not cause y_t in the θ-quantile with respect to the lag-vector of $\{y_{t-1},\dots,y_{t-p},x_{t-1},\dots,x_{t-p}\}$ if

$$Q_\theta\left(y_t \middle| y_{t-1},\dots,y_{t-p},x_{t-1},\dots,x_{t-p}\right) = Q_\theta\left(y_t \middle| y_{t-1},\dots,y_{t-p}\right) \qquad (1)$$

x_t is a prima facie cause of y_t in the θ-th quantile with respect to $\{y_{t-1},\dots,y_{t-p},x_{t-1},\dots,x_{t-p}\}$ if

[6] The description in this section closely follows Nishiyama *et al*. (2011) and Jeong *et al*. (2012).

$$Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\right) \neq Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}\right) \quad (2)$$

where $Q_\theta(y_t|\cdot)$ is the θ-th quantile of y_t depending on t and $0 < \theta < 1$.

Let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. Consequently, the hypotheses to be tested based on definitions (1) and (2) are:

$$H_0\colon\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \quad (3)$$

$$H_1\colon\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \quad (4)$$

Jeong *et al*. (2012) employs the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$ where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null in Eq. (3), which can only be true if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong *et al.* (2012) specify the distance function as follows:

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\right\}^2 f_Z(Z_{t-1})\right] \quad (5)$$

In Eq. (5), it is important to note that $J \geq 0$, i.e., the equality holds if and only if H_0 in (3) is true, while $J > 0$ holds under the alternative H_1 in Eq. (4). Jeong *et al*. (2012) show that the feasible kernel-based test statistic for J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad (6)$$

where $K(\cdot)$ is the kernel function with bandwidth h , T is the sample size, p is the lag-order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t = \mathbf{1}\left\{y_t \leq \hat{Q}_\theta(Y_{t-1})\right\} - \theta \quad (7)$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile of y_t given Y_{t-1}. Below, we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as:

$$\hat{Q}_{\theta}(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{8}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)\mathbf{1}(y_s \leq y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{9}$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

In an extension of the Jeong *et al*. (2012) framework, we develop a test for the 2nd moment. In particular, we want to test the volatility causality running from our considered predictors to U.S. stock returns. Causality in the k-*th* moment generally implies causality in the m-th moment for $k < m$. Firstly, we employ the nonparametric Granger quantile causality approach by Nishiyama *et al*. (2011). In order to illustrate the causality in higher order moments, consider the following process for y_t:

$$y_t = g(Y_{t-1}) + \sigma(X_{t-1})\varepsilon_t \tag{10}$$

where ε_t is a white noise process; and $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. However, this specification does not allow for Granger-type causality testing from x_t to y_t, but could possibly detect the "predictive power" from x_t to y_t^2 when $\sigma(\cdot)$ is a general nonlinear function. Hence, the Granger causality-in-variance definition does not require an explicit specification of squares for X_{t-1}. We formulate null and alternative hypotheses for causality in variance as follows:

$$H_0\text{: } P\left\{F_{y_t^2|Z_{t-1}}\{Q_{\theta}(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{11}$$

$$H_1\text{: } P\left\{F_{y_t^2|Z_{t-1}}\{Q_{\theta}(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{12}$$

To obtain a feasible test statistic for testing the null in Eq. (10), we replace y_t in Eq. (6) - (9) with y_t^2. Incorporating the Jeong *et al*. (2012) approach we overcome the problem that causality in the conditional 1st moment (mean) imply causality in the 2nd moment (variance). In order to overcome this problem, we interpret the causality in higher order moments using the following model:

$$y_t = g(X_{t-1}, Y_{t-1}) + \varepsilon_t \tag{13}$$

Thus, higher order quantile causality can be specified as:

$$H_0\colon\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \quad \text{for } k = 1,2,\ldots,K \tag{14}$$

$$H_1\colon\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \quad \text{for } k = 1,2,\ldots,K \tag{15}$$

Integrating the entire framework, we define that x_t *Granger causes* y_t *in quantile* θ *up to* K*-th moment* utilizing Eq. (14) to construct the test statistic of Eq. (6) for each k. However, it is not easy to combine the different statistics for each $k = 1,2,\ldots,K$ into one statistic for the joint null in Eq. (14) because the statistics are mutually correlated (Nishiyama *et al*., 2011). To efficiently address this issue, we include a sequential-testing method as described Nishiyama *et al*. (2011) with some modifications. Firstly, we test for the nonparametric Granger causality in the 1st moment ($k = 1$). Rejecting the null of non-causality means that we can stop and interpret this result as a strong indication of possible Granger quantile causality-in-variance. Nevertheless, failure to reject the null for $k = 1$, does not automatically leads to no-causality in the 2nd moment, thus we can still construct the tests for $k = 2$. Finally, we can test the existence of causality-in-variance, or the causality-in-mean and variance successively. The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in Eq. (6) and (9) respectively. In our study, the lag order of 1 is determined using the Schwarz Information Criterion (SIC) under a VAR comprising of stock returns and the different predictors. The SIC being parsimonious when it comes to choosing lags compared to other alternative lag-length selection criterion, helps us to prevent issues of over-parameterization commonly associated with nonparametric approaches. Also, the lag-length of one is in line with the predictive regression framework traditionally used in the stock returns literature (Rapach and Zhou, 2013). The bandwidth value is selected using the least squares cross-validation method. Lastly, for $K(\cdot)$ and $L(\cdot)$ we employ Gaussian-type kernels.

3 - Data and empirical findings

The data used in this study includes U.S. stock returns and a comprehensive set of financial and economic indicators as well as migration-related measures. We obtained monthly prices of S&P500 from the Organisation of Economic Corporation and Development (OECD) macroeconomic indicators database for the period 1985:01 – 2015:12. We then take the first difference of the natural logarithm of stock prices and express it in percentages to yield the stock returns. Furthermore, we estimate quarterly stock returns (used in the migration-related analysis) by taking 3-month averages of monthly stock prices to convert it to quarterly data first, before taking first-differences of the logarithms. Working with returns ensures that our dependent variable is stationary[7]. Data on our predictors is derived from Baker *et al*. (2015); all of which are constructed solely based on news data by performing month-by-month[8] searches of newspaper articles containing the terms economic, uncertainty and policy as well as a set of category-specific policy terms: fiscal policy, taxes, healthcare, regulation, monetary policy, government spending, financial regulation, sovereign debt, regulation, trade policy, entitlement programs, debt ceiling, and government shut down. To derive each indicator, a count is made for the number of newspaper articles containing terms, and then divided by the total count of articles in the same newspaper and calendar month. Further details are available at: http://www.policyuncertainty.com/categorical_epu.html. For the financial and economic indicators, the data spans from 1985:01 – 2015:12. The migration fear and migration-related EPU measures are constructed in the same way as the financial and economic indicators, except for the differences in the category-specific terms. Additional details are available at: http://www.policyuncertainty.com/immigration_fear.html. This data is available at a quarterly frequency from 1990:01 to 2015:04. Hence, in total, we have a set of 26 measures of various types of uncertainty, both aggregate and components.

We begin our analysis with the standard linear Granger causality test based on a VAR(1) model specification for purposes of completeness

[7] Complete details of the unit root tests are available upon request from the authors.
[8] Or quarter-by-quarter searches in the case of migration-related measures.

and comparability. The results as reported in Table 1 reveal that apart from national security and financial regulation, there is no evidence of predictability running from the various types of uncertainty measures to U.S. stock returns at standard level of significance. Overall, the evidence is weak in terms of the ability of aggregate EPU and its sub-components to predict U.S. stock returns.

Table 1: Linear Granger Causality Test

	F-statistic	*p*-value
EPU	0.821	0.365
News-based EPU	0.522	0.470
Federal-state-local disagreement	1.972	0.161
CPI disagreement	0.080	0.778
Tax expiration	0.013	0.910
Monetary policy	1.212	0.272
Fiscal policy	2.405	0.122
Taxes	2.064	0.152
Government spending	1.137	0.287
Health care	0.548	0.460
National security	4.712	0.031**
Entitlement programs	0.564	0.453
Regulation	0.009	0.925
Financial regulation	3.015	0.083*
Trade policy	1.334	0.249
Sovereign debt	1.041	0.308
Debt ceiling	0.644	0.423
Government shutdown	1.499	0.222
UK migration-related EPU	0.245	0.622
UK migration fear	0.718	0.399
Germany migration-related EPU	0.176	0.676
Germany migration	0.126	0.724
USA migration-related	1.227	0.271
USA migration fear	0.027	0.870
France migration-related EPU	0.042	0.838
France migration fear	0.770	0.382

Note: ** and * indicates rejection of the null of no Granger causality from the various types of uncertainty measures to U.S. stock market returns at 5% and 10% level of significance respectively

Bearing this in mind, we turn our focus on the nonparametric causality-in-quantiles test. We motivate the use of this approach by checking for the presence of nonlinearity in stock returns itself and in the relationship between stock returns and the considered predictors using the Brock-Dechert-Scheinkman (BDS) (Brock *et al*., 1996) test. According to Table 2, the null hypothesis of independent and identically distributed (*iid*) residuals is rejected at 5% significance level across various dimensions for the majority of the cases. This result suggests strong evidence of nonlinear relationship between stock returns and various types of uncertainty measures, implying that the results from the standard linear Granger causality test are likely to be biased. As a result, there is a need to account for the possible nonlinearity using a nonlinear (nonparametric) test.

Table 2: [Brock *et al.* (1996)] BDS Test

	Dimension				
	2	3	4	5	6
Monthly stock returns	3.667***	4.729***	4.970***	5.101***	5.371***
Quarterly stock returns	-0.077	0.641	1.723*	2.351**	2.565**
EPU	3.694***	4.509***	4.846***	5.151***	5.614***
News-based EPU	3.649***	4.488***	4.831***	5.142***	5.601***
Federal-state-local disagreement	3.491***	4.185***	4.513***	4.815***	5.287***
CPI disagreement	3.627***	4.418***	4.770***	5.074***	5.532***
Tax expiration	3.584***	4.407***	4.758***	5.068***	5.511***
Monetary policy	3.400***	4.159	4.531***	4.888***	5.348***
Fiscal policy	3.724***	4.482***	4.881***	5.214***	5.677***
Taxes	3.749***	4.530***	4.918***	5.235***	5.673***
Government spending	3.661***	4.375***	4.715***	5.041***	5.515***
Health care	3.726***	4.497***	4.899***	5.233***	5.685***
National security	3.746***	4.429***	4.723***	5.061***	5.508***
Entitlement programs	3.702***	4.507***	4.905***	5.271***	5.753***
Regulation	3.586***	4.403***	4.762***	5.084***	5.539***
Financial regulation	3.237***	4.146***	4.474***	4.851***	5.324***
Trade policy	13.287***	14.164***	14.186***	14.782***	15.618***
Sovereign debt	14.020***	14.544***	14.867***	15.453***	16.228***
Debt ceiling	3.603***	4.390***	4.758***	5.074***	5.493***
Government shutdown	13.666***	14.131***	14.174***	14.489***	15.165***
UK migration-related EPU	0.650	1.620	2.572**	3.014***	3.263***

UK migration fear	0.790	1.937*	2.799**	3.232***	3.372***
Germany migration-related EPU	0.688	1.515	2.380**	2.806**	3.024***
Germany migration	0.441	1.499	2.425**	2.861***	3.095***
USA migration-related EPU	0.899	1.796*	2.858***	3.272***	3.454***
USA migration fear	0.642	1.697*	2.704**	3.084***	3.245***
France migration-related EPU	0.642	1.569	2.548**	2.988***	3.175***
France migration fear	1.010	2.150**	3.061***	3.557***	3.886***

Note: The entries indicate the BDS test based on the residuals of an AR(1) model of stock returns and the residuals from the equation of stock returns in a VAR(1) model with the various measures of uncertainties. ***, ** and * indicate rejection of the null of residuals being *iid* at 1%, 5% and 10% levels of significance respectivel.

As can be observed from Figures 1-26, the null hypothesis of no Granger causality-in-mean is rejected at standard level of significance over the entire conditional distribution of stock returns around the mean barring the following cases: tax expiration, national security, financial regulation, sovereign debt, debt ceiling, government shutdown, and the migration-related measures.[9] However, the results of the Granger causality-in-variance suggest that the predictability of U.S. stock returns volatility resulting from the various measures of uncertainty covers the entire distribution except for minor deviations in the tails. In other words, we find evidence of volatility spillovers from EPU and its sub-components to the U.S. stock market. In addition, our findings reveal that uncertainty concerns about entitlement programs, taxes, fiscal policy, health care,

[9] We also analysed the predictability of the migration-related measures on the stock returns and volatility of Germany, UK, and France. The results show that migration-related measures only possess predictive information for UK stock returns. Complete details of these results are available upon request from the authors.

national security, regulation, trade policy, and monetary policy have important effects on volatility of the stock market. Furthermore, our results suggest that migration-related uncertainties increases stock market volatility. Put differently, the flood of immigrants and the fear and uncertainty surrounding it has increased stock market uncertainty. Note that, we can clearly observe the powerful nature of the causality-in-quantiles test employed here by us over the Nishiyama *et al.,* (2011) test carried out by Bekiros *et al.,* (2016), in the sense that we find predictability in returns emanating from various uncertainties, unlike the lack of it reported by Bekiros *et al.,* (2016).

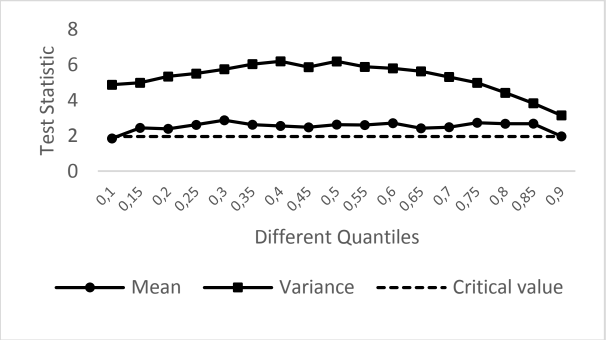


Figure 1: causality-in-quantiles: EPU

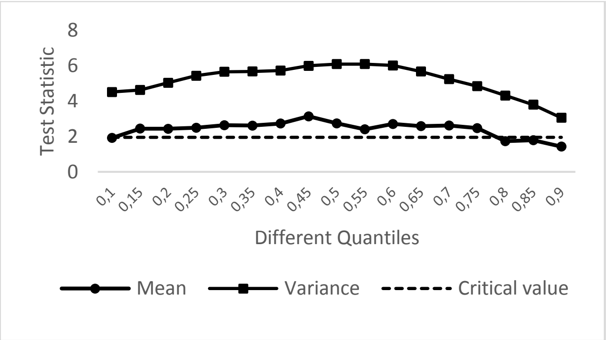


Figure 2: causality-in-quantiles: News-based EPU

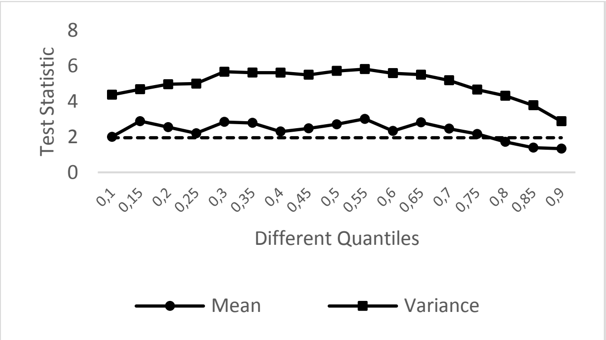


Figure 3: causality-in-quantiles: Federal-state-local disagreement

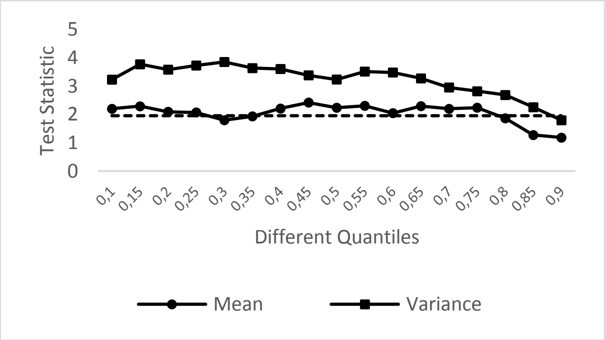


Figure 4: causality-in-quantiles: CPI disagreement

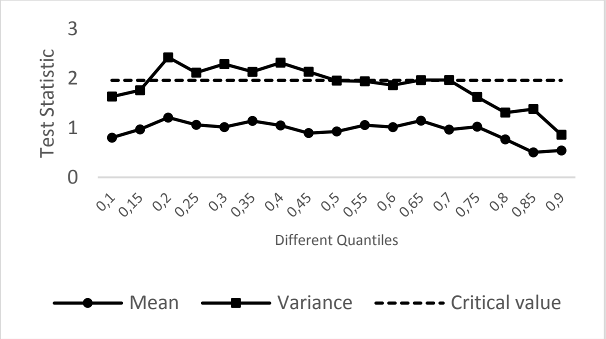


Figure 5: causality-in-quantiles: Tax expiration

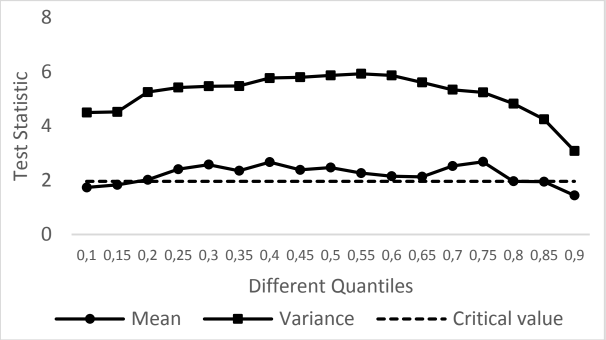


Figure 6: causality-in-quantiles: Monetary policy

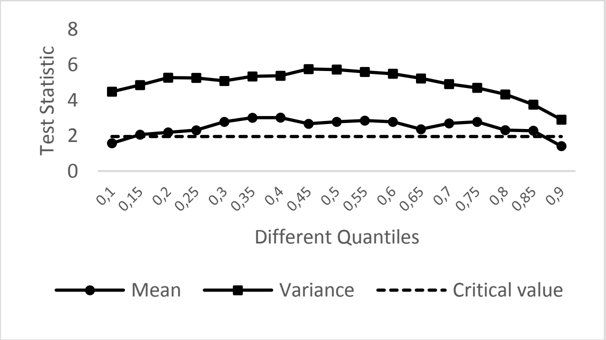


Figure 7: causality-in-quantiles: Fiscal policy

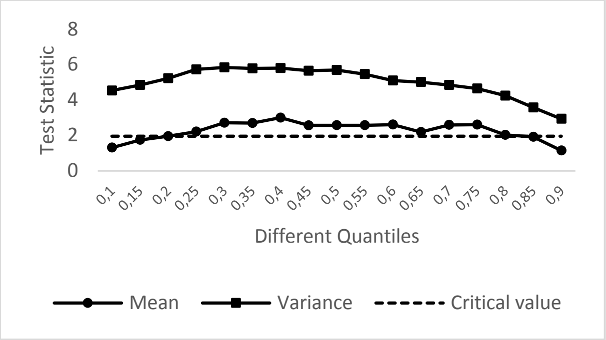


Figure 8: causality-in-quantiles: Taxes

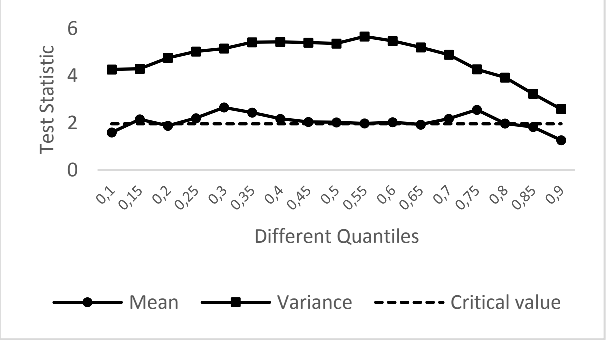


Figure 9: causality-in-quantiles: Government spending

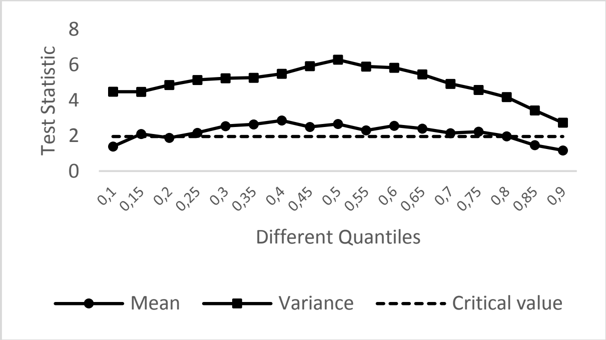


Figure 10: causality-in-quantiles: Health care

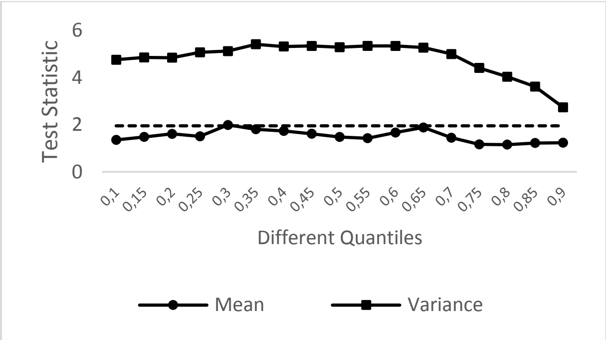


Figure 11: causality-in-quantiles: National security

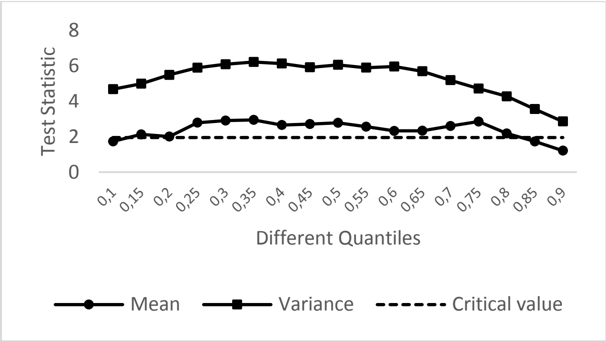


Figure 12: causality-in-quantiles: Entitlement programs

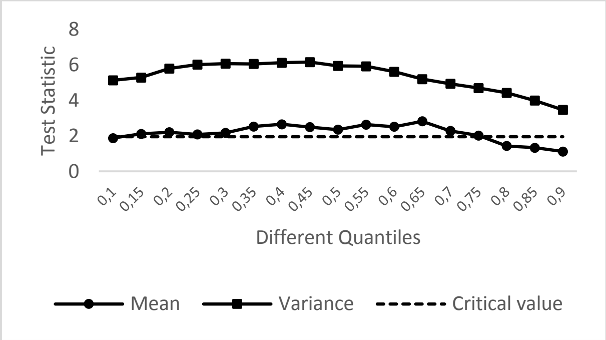


Figure 13: causality-in-quantiles: Regulation

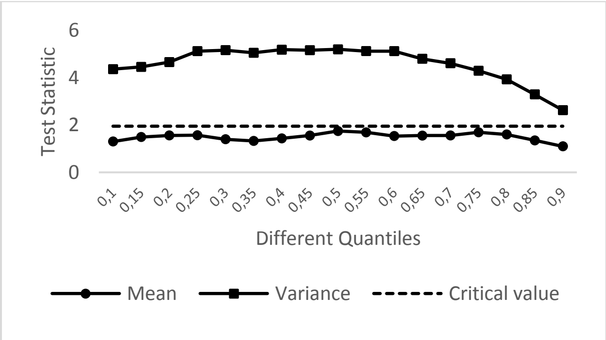


Figure 14: causality-in-quantiles: Financial regulation

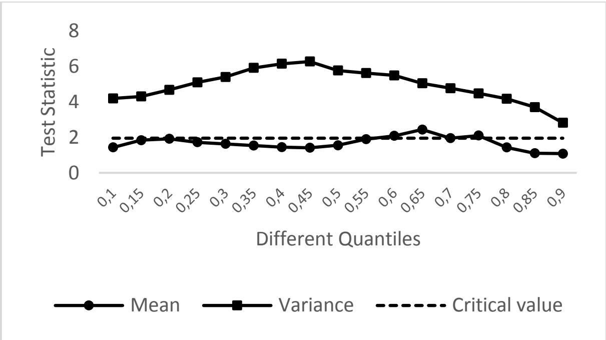


Figure 15: causality-in-quantiles: Trade policy

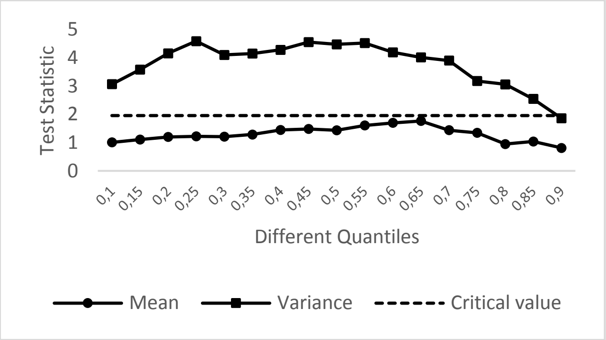


Figure 16: causality-in-quantiles: Sovereign debt

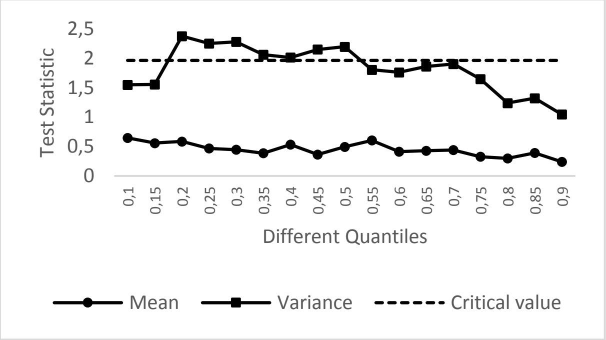


Figure 17: causality-in-quantiles: Debt ceiling

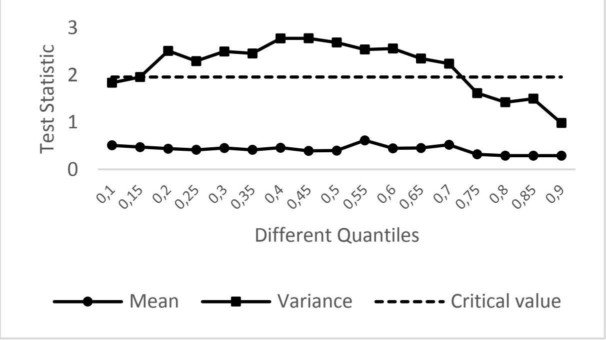


Figure 18: causality-in-quantiles: Government shutdown

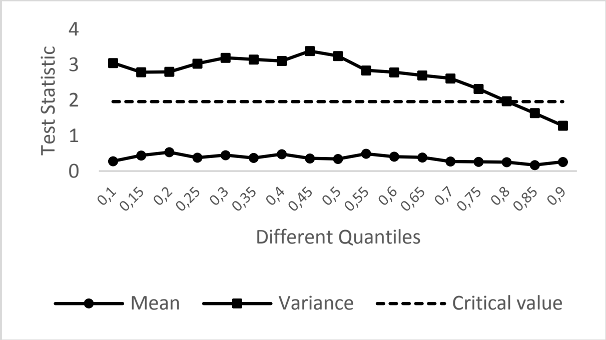


Figure 19: causality-in-quantiles: UK migration-related EPU

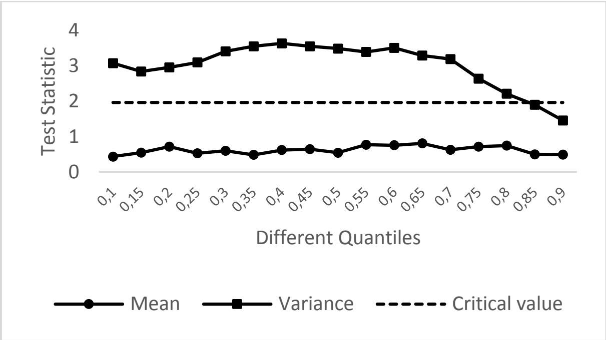


Figure 20: causality-in-quantiles: UK migration fear

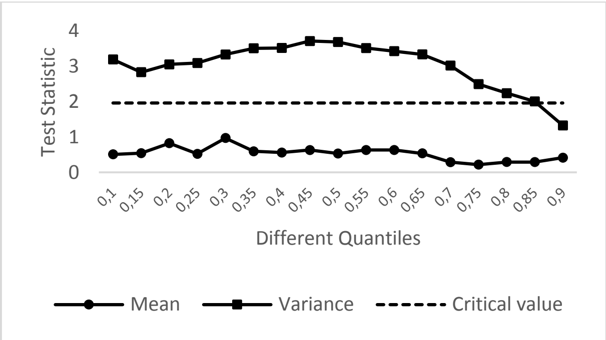
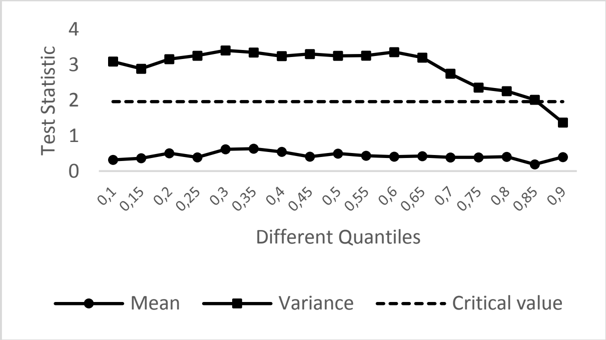


Figure 21: causality-in-quantiles: Germany migration-related



EPU Figure 22: causality-in-quantiles: Germany migration fear

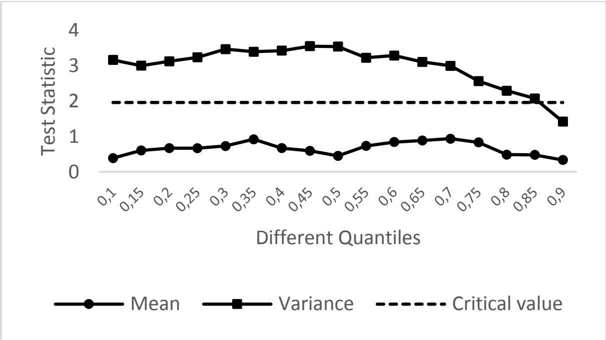
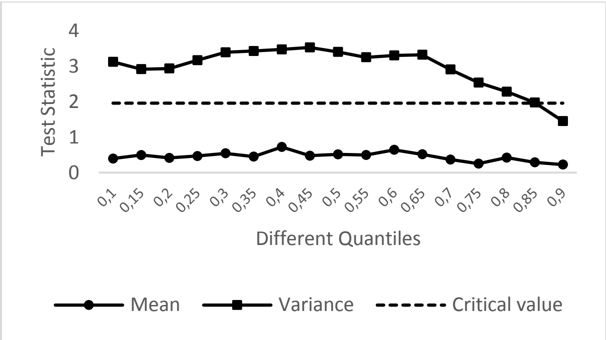


Figure 23: causality-in-quantiles: USA migration-related



EPU Figure 24: causality-in-quantiles: USA migration fear

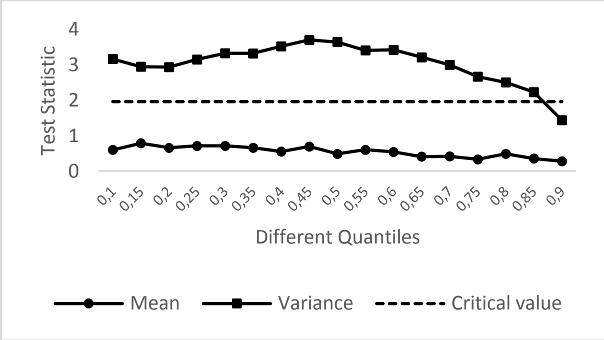


Figure 25: causality-in-quantiles: France migration-related EPU

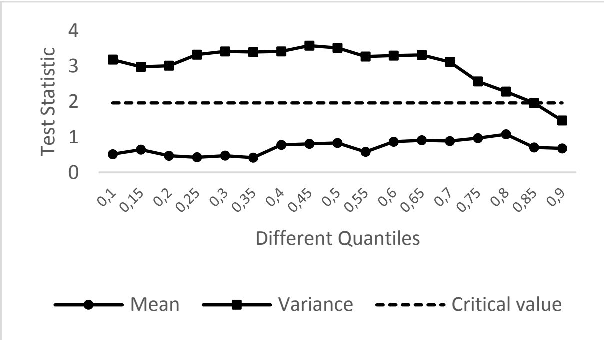


Figure 26: causality-in-quantiles: France migration fear

4 – Conclusion

Experts in finance and academic researchers continue to seek for predictors that contain relevant information and thus can improve stock returns predictability. Predicting stock returns has significant implications for asset allocation, investment performance, and for testing market efficiency. Further, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices, with it being the most important variable in the pricing of derivative securities. Predicting volatility is also important from the perspective of financial risk management.

In this regard, we analyse whether a comprehensive set of financial and economic uncertainty indicators, as well as migration-related measures can predict U.S. stock returns and volatility. To achieve that, we employ the nonparametric causality-in-quantile test proposed by Balcilar *et al*. (2016, forthcoming a) that combines the frameworks of Nishiyama *et al*. (2011) and Jeong *et al*. (2012). Results from the standard linear Granger causality test suggest that, apart from uncertainty about national security and financial regulation, there is no evidence of predictability running from the various types of uncertainty measures to U.S. stock returns. However, given the existence of inherent nonlinearities in our examined series, the linear model is likely to be misspecified. For this reason, we use the nonparametric causality-in-quantile test which reveals that aggregate economic policy uncertainty together with its sub-components possesses important information for predicting U.S. stock returns and volatility barring few cases. In general, the prediction is strongest for returns volatility than for returns. Moreover, we document the ability of the recently developed migration-related EPU and migration fear measures for predicting financial market volatility. Our study therefore, provides evidence that the level of aggregate policy uncertainty and its sub-components can affect stock market returns, as well as, its volatility.

As part of future research, it would be interesting to analyse whether our results continue to hold over and out-of-sample period as well, since in-sample predictability does not guarantee forecastability (Rapach and Zhou, 2013).

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